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Trading Patterns in the European Carbon Market:

The role of trading intensity and OTC transactions

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Abstract

This paper examines the effect of trading intensity and OTC transactions on expected market conditions in the early development period of the European Carbon futures market. Past duration and trading intensity are used as information related order flow variables in modeling time between transactions in two new specifications of Autocorrelation Conditional Duration (ACD) models. This allows for specific investigation of non-linear asymmetric effects on expected duration and the impact of OTC transactions. Evidence is presented of two main types of trading episodes of increased and decreased trading intensity. Both have a significant impact on price volatility which increases further if an OTC transaction intrudes. OTC transactions also play a dual role. They slow down trading activity in the short term (over the next five transactions) but increase it substantially in the long term (over ten transactions). Both the liquidity and information price impact components increase following an OTC trade, but the information impact is greater. Price volatility calms down faster than liquidity effects following an OTC trade, and this is more pronounced in ECX and in Phase II. The combined evidence points towards increased market depth, efficiency and maturity of the trading environment.

EFM codes: 320, 360, 420

Key Words: *Carbon Market, Duration Modeling, Ultra-High-Frequency Data*

1. Introduction

This paper investigates market depth, trading activity, liquidity, price volatility and the role of OTC transactions in the early development period of the European carbon market. Three enhanced auto-correlated duration (ACD) specifications are formulated to describe possible distinct effects of liquidity on trading dynamics of the two largest trading platforms of Carbon allowances, namely the European Climate Exchange (ECX) and Nord Pool (NP). Two of these specifications are formulated to identify high and low states, or regimes, of duration (time between trades) and of trading intensity (duration-weighted volume), and the third incorporates distinct characteristics of OTC trades. The emphasis is on identifying types of liquidity trading episodes and on investigating their duration, volume, intensity, and price impact and volatility characteristics. Studying the anatomy of these episodes would allow for assessment of the markets' ability at absorbing duration and intensity shocks. Further, tracing the development of episode characteristics and the markets' ability at absorbing liquidity shocks would allow for the detection of possible differences in development and efficiency between the two main trading platforms, ECX and NP, and across their two first phases (Phase I: 2005-2007 and Phase II: 2008-2013). This would highlight the nature of the relationship between variations in liquidity and price volatility and the role of the distinct characteristics of OTC trades in trading activity in the carbon market. Specific to the latter is the question of whether high intensity and OTC trades have a distinct effect on trading activity and an impact on price volatility, which would have implications on their role in the resolution of uncertainty and pricing efficiency.

In December 1997 the vast majority of industrialised and EU countries has ratified a treaty known as “The Kyoto Protocol” aiming at the reduction of their green-house related emissions. The protocol establishes “flexibility mechanisms” for diminishing costs and achieving emission targets.¹ The European Union Emissions Trading Scheme (EU ETS), which is the mechanism that has been set up to achieve these objectives in Europe, has gradually gained complexity and has become the

¹ For relative growth in the mechanisms see, for example, Carbon Report, 2009, at www.pointcarbon.com. The three mechanisms are the Joint Implementation mechanism (JI) (under art.6), the Clean Development mechanism (CDM) (under art.12) and the Emissions Trading Scheme (ETS) (under art.17). Phase I (2005-2007) is the pilot period, Phase II (2008-2012) is the commitment period and Phase III (2013-2020) is the post commitment period for re-evaluation and further adjustments. Further information is found in Mansanet-Battaller and Pardo (2008) and IETA annual reports (2009).

largest emissions trading scheme worldwide.² This futures market of emission allowances has some unique features. First, it is a truly 'cap and trade' system, where overall allowances are capped in line with emission abatement targets and applies to specific industrial sectors. The overall quantity, and consequently prices and trading activity, are, therefore, politically influenced. Second, the market is less liquid than other financial markets and prices are highly influenced by economic outlook. Third, standardized contracts are traded simultaneously in mainly two non-synchronous but overlapping markets. Finally, a non-unique feature is that both markets permit entry and registry of over-the-counter positions.³ These features affect pricing and liquidity in various ways, of which those related to the last three features in particular are investigated in this paper.

Several studies have been conducted on the carbon market. Kruger et al. (2007) and Chevallier (2009), amongst others, provide a general description of the trading mechanisms and several stylized facts. Christiansen (2005) and Mansanet-Bataller et al. (2007), amongst others, examine price dynamics, and report strong links with the prices of related commodities. Uhrig-Homburg and Wagner (2006) and Daskalakis et al. (2009), amongst others, analyse political influence on market efficiency. A growing strand of literature focuses on market microstructure issues such as the intraday price formation (Benz and Hengelbrock, 2008) and intraday price leadership between alternative compliance units (Bataller et al., 2010). Some liquidity issues have also been investigated. Mizrach and Otsubo (2011), for example, report increasing liquidity with increasing price impact; Ibikunle et al. (2011) contends that this is not necessarily due to increased volume, and Bredin et al. (2011) suggest that it might be related to information dissemination between OTC and screen trades. In particular, although Benz and Hengelbrock (2008) and Bredin et al. (2011) take into account event time (*i.e.*, irregularly spaced events over time) duration is not yet fully investigated in EU ETS using ACD models.⁴ Kalaitzoglou and Ibrahim (2012) is the exception. They model duration using a three-

² In this trading mechanism, a participating state allocates a certain amount of "European Union Allowances" (EUAs) across its emitting installations. Each EUA entitles the holder to emit one ton of CO₂ equivalent of Green House Gases (GHGs).

³ Exchange for Physical (EFP) and Exchange for Swap (EFS) facilities are offered to OTC allowance holders in order to register their positions. Further information can be found at <http://www.ecx.eu/index.php/Exchange-for-Physical-EFP>.

⁴ In lower frequency data, time intervals are fixed and all relevant information is either aggregated or attempts are made at synchronising it. However, in Ultra-high-frequency datasets duration varies and would have informational content. In developing the ACD framework for the proper modeling of economic time, Engle and Russell (1998) highlight the differences between economic and calendar time and the deficiencies of considering calendar time intervals in modeling economic events, especially at high frequencies.

regime smooth transition ACD model with the main aim of identifying different groups of traders through variations in non-price related order flow variables. This paper also models event time through a combination of regime-switching and non-regime switching ACD models, but focuses instead on the identification of liquidity episodes and the investigation of their impact on prices and price volatility within different regimes of trading intensity. Further, the speed by which the markets absorb duration and intensity shocks varies across markets and phases, especially when OTC trades intrude. A comparison across markets and phases of the liquidity and price characteristics of trading episodes, therefore, reveals distinct features of market development and carries implications on pricing efficiency. In addition, proper modeling of time between trades considers the informational content of transaction time and this has a variety of implications that are relevant to market and regulatory authorities, not least of which are suggestions for enhancing monitoring systems and improving market and price efficiency.⁵ Better understanding of liquidity and pricing dynamics would also enhance inventory management and order submission strategies by traders and investors as a consequence of better informed management of execution, liquidity and adverse selection risks.

The remainder of this paper is organised as follows. Section 2 presents the methodology; Section 3 presents the data and a preliminary analysis; Section 4 presents a discussion of the implications of the estimation results and analyses of liquidity episodes; and Section 5 concludes.

2. Methodology

Engle and Russell (1998) propose ACD models for high frequency irregularly spaced data. They model the inter-trade interval, duration x_i , as a dependent point process, where the conditional mean, $E(x_i|x_{i-1}, \dots, x_1)$, varies over time as a function of past durations. The ACD is formulated as:

$$x_i = \psi_i \varepsilon_i \quad (1)$$

$$\psi_i = \psi(x_{i-1}, \dots, x_1; \varphi_1) \quad (2)$$

⁵ Viswanathan (2010) raises the importance of regulatory and monitoring issues, arguing that the driving forces of Carbon trading need to be understood and regulated to ensure viability. He argues that carbon markets need a regulatory approach that restricts manipulation while simultaneously allowing innovation to enhance liquidity. A non-regulated and non-transparent market would be liquid but inaccurate in terms of price. In contrast, strict regulation would increase price accuracy but not liquidity. Both would result in a divergence from EU ETS's initial purpose.

$$\varepsilon_i \sim i.i.d. \text{ with density } f(\varepsilon_i; \varphi_2) \quad (3)$$

where, x_i is duration, ψ_i is expected duration, ε_i is standardized duration and φ_1 and φ_2 are vectors of parameters. The general model allows for various specifications of the conditional mean, as a function of past durations. Engle and Russell use a linear ARMA(1,1) specification. The model also allows for various density functions for ε_i (with positive support).⁶ In this study, two non-linear specifications of the mean, and the exponential (E), Weibull (W) and generalized-gamma (G) distributions are used for the standardized duration.⁷ The two mean specifications are presented next.

2.1 The Smooth Transition Box-Cox ACD (ST-BCACD) Model

In order to account for likely non-linearity and asymmetric effects of past durations on expected durations an enhanced version of the non-linear Box-Cox ACD (BCACD) model of Dufour and Engle (2000) is considered.⁸ This model, dubbed the Smooth Transition (ST) BCACD, is written as follows:

$$\ln \psi_i = \omega + \sum_{j=0}^m a_j (\varepsilon_{i-j})^{\delta_j'} + \sum_{j=0}^q \beta_j \ln \psi_{i-j} \quad (4)$$

$$\delta' = \delta_1 * (1 - G(S_i; g, s)) + \delta_2 * G(S_i; g, s) \quad (5)$$

$$G(S_i; g, s) = (1 + \exp\{-g(S_i - s)\})^{-1} \quad (6)$$

where, δ' , indicates the size of the effect of past realized durations on expected durations and, in this specification, it is allowed to vary within a range determined by an estimated lower bound of δ_1 and an estimated upper bound of δ_2 . The non-linearity parameter δ' , therefore, is a weighted average of the lower and upper bound coefficients δ_1 and δ_2 , and the 'weights' are determined by the smoothing

⁶ Engle and Russell (1998) use the linear ARMA specification and the Exponential and Weibull distributions. This simple specification has been subsequently expanded and generalised (e.g., Meitz and Terasvirta, 2006), and more flexible density functions proposed (e.g., Hujer and Vuletic, 2007).

⁷ The exponential is $f(x_i | x_{i-1}, \dots, x_1; \theta) \equiv 1/\psi_i \cdot \exp(-x_i/\psi_i)$,

the Weibull is $f(x_i | x_{i-1}, \dots, x_1; \theta) \equiv \gamma/\chi_i \cdot [x_i \Gamma(1 + 1/\gamma)/\psi_i]^\gamma \exp(-[x_i \Gamma(1 + 1/\gamma)/\psi_i]^\gamma)$ and

the generalized-gamma is $f(x_i | x_{i-1}, \dots, x_1; \theta) \equiv \gamma/\chi_i \Gamma(\lambda) \cdot [x_i \Gamma(\lambda + 1/\gamma)/\psi_i]^\lambda \exp(-[x_i \Gamma(\lambda + 1/\gamma)/\psi_i]^\lambda)$,

where $\Gamma(\cdot)$ is the gamma function with parameters $\gamma (\gamma > 0)$ and $\lambda (\lambda > 0)$. These three distributions are nested. If $\lambda=1$ the Generalized Gamma distribution reduces to the Weibull, and if $\gamma=1$ the Weibull reduces to the Exponential.

⁸ The original BCACD of Dufour and Engle (2000a) is $\ln \psi_i = \omega + \sum_{j=0}^m a_j (\varepsilon_{i-j})^\delta + \sum_{j=0}^q \beta_j \ln \psi_{i-j}$. Note that this specification has δ as a constant. When $\delta=1$ the BCACD reduces to the linear ACD(m, q) and when $\delta \rightarrow 0$ it reduces to the LOGACD of Bauwens and Giot (2000).

function $G(S_i; g, s)$. This function depends on a threshold variable S that captures characteristics of order flow, with a specific threshold value, s , that dissects these order flow characteristics into two regimes of high and low states. The function G also depends on the smoothness parameter g , which determines the extent of gradual adjustment around the threshold value s , with lower values indicating smoother transitions between the two regimes. When $S_i \ll s$, then $G(S_i; g, s) \rightarrow 0$ and $\delta' \rightarrow \delta_1$. In contrast, when $S_i \gg s$, $G(S_i; g, s) \rightarrow 1$ and $\delta' \rightarrow \delta_2$. In this manner, therefore, the threshold variable is allowed to have a non-linear impact on expected durations since δ' is allowed to vary depending on characteristics of order flow. In this study two variables that capture characteristics of order flow are used as the threshold variable S : past durations and trading intensity.⁹ When past durations are used the model is dubbed Self Exciting Smooth Transition (SEST)-BCACD, and when trading intensity is used the model is dubbed Intensity Smooth Transition (IST)-BCACD.¹⁰

2.2 The Box-Cox ACD Over The Counter (BCACD-OTC) Model

In order to study the impact of OTC trades more carefully an extension of the BCACD model is employed. In this model the mean specification of duration, Eq. (4) above, is replaced with

$$\ln \psi_i = \omega + \sum_{j=0}^m (a_j + \zeta_j * I_{i-j}) * (\varepsilon_{i-j})^{\delta_j} + \sum_{j=0}^q \beta_j \ln \psi_{i-j} \quad (7)$$

where

$$I = \begin{cases} 0, & \text{for normal transactions} \\ 1, & \text{for OTC transactions.} \end{cases}$$

and ζ (zeta) is a parameter that captures the distinct effect of OTC transactions. This parameter revises the AR coefficient, α , when the last transaction is an OTC transaction. If zeta is statistically significant, then OTC transactions convey specific information and play a distinct role in formulating duration expectations. Further, the sign of zeta carries interpretation. If zeta is positive (negative), then an OTC transaction causes expected duration to be longer (shorter), and this increase (decrease) can be a result of either a reduction (increase) in liquidity or a rational reaction to increased

⁹ Trading intensity is defined as volume weighted duration (*i.e.*, the ratio of trade size over trade duration).

¹⁰ Similar to Meitz and Teräsvirta (2006) the magnitude of past durations allow for re-adjustments of clustering. In addition, the microstructure literature suggests that investors gain information from observing past trading activity. Fluctuations in trading might reveal price relevant information, which might change investors' trading patterns. The magnitude of the particular event (*e.g.*, Easley and O'Hara, 1992; Dufour and Engle, 2000 and Madhavan, 2000) and the variations in the learning speed of the market participants (*e.g.*, Vives, 2008 and Kalaitzoglou and Ibrahim, 2012) might result in lagged or asymmetric effects. Here, trading intensity is used to proxy for liquidity variations, or how "thick" the market is after each trade.

(decreased) information flow. For example, a positive zeta could mean that an OTC transaction is interpreted by market participants as a significant information inflow and, consequently, would instil reluctance to trade for fear of losing money by trading with more informed traders. In contrast, since the majority of OTC transactions are very large (on average, 1.9 to 4.1 times the size of non-OTC trades), a positive sign for zeta, and subsequent longer expected durations, could indicate that OTC transactions “exhaust” current liquidity dictating a longer time span for the market to replenish depleted depth. A negative zeta can also be interpreted as an information flow but for a different reason. OTC transactions can be information 'bearers' that release important information which certain market participants can take advantage of (perhaps on account of others who are slower to react; see Kalaitzoglou and Ibrahim (2012)). This increased activity decreases expected duration.

Estimation is carried out by maximising the log-likelihood function using the Broyden, Fletcher, Goldfarb and Shanno (BFGS) optimisation algorithm with numerical derivatives. The in-sample goodness of fit is tested by the likelihood ratio (L) test and the Bayesian information criteria (BIC). Wald tests are used to examine whether ζ is zero and whether δ_1 , δ_2 , and the distribution parameters, γ and λ , are equal to one.

3. Data

3.1 Data collection and preparation

The data employed in this study concerns the two largest exchanges operating during the early development period of the EU ETS market, namely the European Climate Exchange (ECX) and Nord Pool (henceforth, NP). The datasets cover the period from market inception, namely January 2005, to the end of 2008.¹¹ This period includes the whole of Phase I and the first year of Phase II. These phases are examined separately in each market. The data consists of date, time stamp, price, volume, buy or sell trade indicator, and an OTC indicator for all transactions recorded for the futures contract with December 2008 maturity, which is the most liquid, by far.¹² Every futures contract, 'lot',

¹¹ The year 2005 was the first year of operation for the EU ETS, and as the market was in a very early stage and rather unstable, all observations of that year are omitted.

¹² The precise maturity date is the first business day of December on NP and the last Monday of December on ECX. These contracts can be used for compliance reasons on April 2009. For further information refer to www.ecx.eu.

corresponds to 1000 EUAs, and every EUA gives the right to emit 1 ton of CO₂ equivalent in greenhouse gases. Settlement is guaranteed by a clearing house, and counterparty risk is mitigated by margin accounts.¹³ Prices in both exchanges are quoted in Euros and the minimum tick is €0.01. Trading is continuous from Monday to Friday, with trading hours 08:00-18:00 Central European Time (CET) on ECX and 08:00-15:30 on NP.

The microstructure literature poses some issues concerning data manipulation that need to be taken into account. First, all transactions out of the official trading hours are excluded, since only trading patterns within the normal continuous trading period are examined. Second, duration is calculated in seconds and the overnight period is excluded in order to assume continuous trading.¹⁴ Third, in order to deal with the asymptotic convergence to minus infinity at zero of the logarithmic function, transactions with zero durations are omitted and all associated variables (marks) are aggregated into the subsequent transaction.¹⁵

Another important issue is the treatment of outliers. Phase I was the pilot period for the EU ETS and some unusual observations, such as extremely long durations or high volumes, are observed. In addition, the construction of continuous trading data sets that ignore non-trading periods creates some artificial observations, such as durations longer than the official trading hours. Therefore, the following filters are applied. First, all observations with duration longer than the official trading period are omitted. Second, all observations, with durations longer (shorter) than the mean plus (minus) five standard deviations are considered as outliers and are omitted. The same procedure is also applied to price. Finally, all observations with volume larger than 500 contracts are omitted to account for recording discreteness. This filtering procedure generates four data sets: Phase I

¹³ The ICE Clear Europe, clearing fee is €3.50 and €3.00 per lot per side in ECX and NP, respectively.

¹⁴ For example, the time elapsing between 16:59:30 of day t-1 and 07:00:10 of day t is considered to be only 40 seconds. The same rule is applied in all days without transactions, such as weekends and holidays. They are treated as if they do not exist. There is a debate on the implications of either including or excluding these time intervals. Specifically, papers, such as Ben Sita (2010), maintain that when non-trading periods, such as weekends, are considered in the data sets, heteroskedasticity of a known form is imported because of the inherent seasonality involved. In contrast, Manganeli (2005) argues that the elimination of the overnight period results in the loss of important information.

¹⁵ The term “aggregation” refers to volume, where the value used in the final dataset is the sum of all relevant values from the omitted transactions. For example, four transactions with the same time stamp where the associated volume for each one is 5 contracts would be considered as a single transaction with an aggregated volume of 20 contracts. In addition, the price, trade sign and the dummy variable that captures OTC transactions are also affected. However, the majority (over 90 per cent) of these transactions have similar values (*i.e.*, 90 per cent of transactions with the same time stamp have the same price, trade direction and type (whether OTC or non-OTC)). In these cases, only the relevant variables of the first transaction are taken into account.

(1/2/2006-31/10/2007) with 42606 observations for ECX and 3804 for Nord Pool; and Phase II (1/2/2008-31/10/2008) with 91264 observations for ECX and 3606 for Nord Pool. Henceforth, these market phases will be referred to as ECX I, ECX II, NP I and NP II.

Finally, the vast majority of the microstructure literature reports a strong intraday trading seasonality, with markets being more active than average immediately after opening and just before closing. Figure 1 presents the intraday variations of inter-trade durations in both markets and phases. All four panels indicate that duration exhibits the usual inverse U-shape intraday pattern in both markets and phases. Market activity is more intense during the opening and closing sessions, while duration is notably longer during the lunch break. This introduces heteroskedasticity in the time series of duration and trading intensity and this needs to be taken into account. Accordingly, the diurnal adjustment suggested by Engle (2000) is applied to the time series of both duration and trading intensity. Briefly, this procedure regresses raw duration and trading intensity on a cubic spline function of the daily trading time. Raw values are then divided by fitted values and the time series of this ratio is taken as the diurnally adjusted series.¹⁶ The models discussed in Section 2 are then estimated with diurnally adjusted series as inputs.

3.2 Preliminary analysis

This section presents some preliminary features of the of the data series under investigation to provide the foundations of the parametric analysis. Table 1 reports the descriptive statistics of the variables employed and reveals that the two markets, as well as the two phases, differ significantly. First, average duration is significantly lower in ECX than in NP, and in Phase II than Phase I. Second, the

¹⁶ Specifically, each trading day is divided into five time intervals; each of two hours long. The nodes, or time benchmarks, used, are 10:00:00, 12:00:00, 14:00:00, 16:00:00, 18:00:00 CET, which represent 36,000, 43,200, 50,400, 57,600 and 64,800 seconds after midnight, respectively. Raw durations ($d_i = t_i - t_{i-1}$) and raw trading intensity, $k_i = v_i/d_i$, where v_i is the number of contracts per transaction, are then regressed on the following time function, in order to obtain $E[d_i|f(t)]$ and $E[k_i|f(t)]$.

$$f(t) = \beta_0 + \sum_{m=1}^3 \sum_{j=1}^5 \beta_j (t - n_j)^m,$$

where $j = 1, \dots, 5$ stands for the five nodes used, $m = 1, 2, 3$ are the powers that characterise a cubic spline and n_j 's are five dummy variables, constructed as:

$$n_j = \begin{cases} t - k_j & \text{when } k_{j-1} < t < k_j \\ 0 & \text{elsewhere} \end{cases}.$$

Following the estimation of β_0 and β_j 's, durations and trading intensity are normalized, or diurnally adjusted, as follows.

$$\begin{aligned} x_i &= d_i / E[d_i|f(t)], \\ S_i &= k_i / E[k_i|f(t)], \end{aligned}$$

where x_i is the diurnally adjusted durations and S_i is the diurnally adjusted trading intensity.

average transaction size (volume) is larger in ECX than in NP and decreases in Phase II, especially in ECX. The shorter duration and larger volume lead to higher trading intensity in ECX (0.69 versus 0.27 in NP) and increases in Phase II (but not in NP).¹⁷ Third, average price is slightly lower in ECX than in NP, and increases in Phase II. Finally, duration, volume and trading intensity exhibit the typical over-dispersion (standard deviations larger than the mean) and high skewness and kurtosis that characterise many high frequency variables. Overall, these values, together with the relative transaction numbers mentioned in the previous section and the evolution over time of total volume shown in Panels A and B of Figure 2, confirm the fact that ECX is far larger and more liquid than NP, and that Phase II is more active than Phase I.¹⁸

4. Empirical Results

Four models are estimated for each market and phase: BCACD, SEST-BCACD, IST-BCACD and BCACD-OTC. In addition, each model is estimated in three versions with different error distributions: exponential (E), Weibull (W) and generalised gamma (G). Tables 2 and 3 present the estimation results for ECX and NP, respectively. Implications of the results on trading episodes and differences between the two most prominent trading environments are discussed in the following subsections.

4.1 Non-linearity and OTC transactions

A few observations from the estimation results in Tables 2 and 3 are in order. First, estimates of the ARMA parameters, ω , α and β are all highly significant confirming the autoregressive nature of durations. Second, the maximum log-likelihood values (L) increase substantially across distributions from E to G for all models and for both markets and phases.¹⁹ This confirms that the best distribution for the errors, amongst the three considered, is the most generic generalised gamma. Comparing the values of L across models estimated with this distribution also reveals that a progressively better fit is

¹⁷ This is consistent with Mizrach and Otsubo (2011) who report an increasing liquidity in the EU ETS. Trading intensity as the number of traded contracts per unit of time is a natural measure of liquidity and an indicator of market depth since higher values mean that large orders are matched faster.

¹⁸ Nord Pool struggled to keep market share and was acquired in 2008 by NASDAQ OMX.

¹⁹ Likelihood Ratio (LR) tests ($2 \times$ difference in L between any pair of models) are all highly significant given a 5% critical value of 3.84 (when comparing E with W or W with G) or 5.99 (when comparing E with G).

observed across models in the order in which the models are tabulated from left to right, viz., BCACD, SEST-BCACD, IST-BCACD and BCACD-OTC. The corresponding decrease in the values of the *BIC* criterion further confirms this progressive increase in goodness of fit across error distributions and models. These results have two main implications. First, the effect of past durations on non-linearity, as captured by SEST-BCACD, is significant, and the effect of past trading intensity on non-linearity, as captured by IST-BCACD, is more significant.²⁰ Second, the effect of OTC transactions on expected duration, as modelled by the BCACD-OTC, is even more significant than the effects of past duration or intensity on non-linearity. This is clear evidence, therefore, that non-linearity exists, is affected by past duration and trading intensity, and OTC transactions have a more significant impact on trading dynamics in both markets and phases. Accordingly, recent information in order flow is relevant in predicting the duration of next trades, but an immediately preceding OTC trade is even more relevant. These general features are investigated further in separate sections next, with particular focus on the estimation results of the best-specified model with gamma distribution, viz., the BCACD-OTC(G).

4.2 Non-linear asymmetries, liquidity, momentum and market depth and maturity.

Estimation results reveal that the markets' trading processes differ. Estimates of the distribution shape and scale parameters γ and λ in the BCACD-OTC(G) are statistically significant for both markets and phases. The magnitude of these parameters, and that of their product, determines the shape of the hazard function (the probability of a transaction to occur in the next instant, *i.e.*, the instantaneous transaction rate) of duration that describes the trading process in each market. Specifically, a value less than one for the product $\gamma\lambda$ when γ is less than one would indicate a hazard function that monotonically decreases with increases in duration (*c.f.*, Lunde, 1999) and, consequently, a declining probability of a transaction to occur as duration increases, which implies a prolonging of relative inactive episodes. In contrast, a value greater than one for $\gamma\lambda$ when γ is less than

²⁰ As explained in Section 2, past durations and trading intensity are the variables proposed in SEST-BCACD and IST-BCACD, respectively, to affect the parameter δ' which is the power on past realised durations in the AR term of the ACD model. Estimates of δ_1 and δ_2 in both the SEST-BCACD and the IST-BCACD models are far less than one in both markets and phases (Wald tests, reported in the H(0) section of Tables 2 and 3, confirm).

one would indicate an inverted-U-shaped hazard and initially a non-monotonically increasing probability of a transaction to occur as duration increases up to a certain value, followed by a non-monotonically decreasing probability as duration increases beyond this value. In this latter case, therefore, the market experiences an urge to be active as activity slows down, but if activity slows down by much then the market enters into inactive episodes. Estimates of γ and λ reported in Tables 2 and 3, show that γ is less than one in both markets and phases, but imply that the product $\gamma\lambda$ is greater than one in ECX and less than one in NP. Thus, the hazard is in inverted-U shaped in ECX and monotonically decreasing in NP. If duration decreases and activity slows down it is more likely for a transaction to occur in ECX than in NP. Accordingly, it is less likely for trading in ECX to enter an inactive stage and, consequently, prolonged inactive stages are less likely to occur in ECX than in NP. This clearly reveals that ECX is more liquid and trading activity is more difficult to significantly slow down than in NP. Coupled with relatively much larger transaction size (*see* Table 1) and number of trades (*see* Section 3.1) ECX is, therefore, a deeper market since larger orders are traded faster with less chance of consequential slow-down in trading activity. Finally, since market depth is an integral aspect of market maturity for fledgling markets, these results, therefore, also offer preliminary indication that ECX is more mature than NP.

4.3 Episodes of trading activity and their characteristics

Although the Smooth Transition models, SEST-BCACD and IST-BCACD, do not fit as well as the BCACD-OTC, they still fit better than the traditional BCACD, and this sub-section presents an analysis of their parameter estimates that indicates the presence of high and low activity episodes in the market. The focus is on estimates of the coefficients s , δ_1 , δ_2 , and g reported in Tables 2 and 3.

The parameter δ' captures the scale of the effect of past realised duration on expected duration, and has lower and upper bounds of δ_1 and δ_2 , respectively. The range is dissected into two regimes/states of long and short past realised duration in the SEST-BCACD model and into two regimes/states of high and low trading intensity in the IST-BCACD model. The dissection occurs at the estimated parameter value s of the threshold variable S in each model. In SEST-BCACD the threshold variable is past duration, and in IST-BCACD it is trading intensity. First, SEST-BCACD(G)

estimates of s are always lower for ECX than for NP, and lower in Phase I than in Phase II in both markets. Second, estimates of δ_1 and δ_2 by the same model are also lower in ECX than in NP. Thus, the duration expected for the next transaction is affected more by longer than by shorter past duration, and this is more pronounced in ECX than NP, and in Phase II than in Phase I. This implies that inactive market stages (clusters of long durations of regime 2) are prolonged, while short durations in active market stages (clusters of short durations of regime 1) lead to even shorter expected durations, which creates episodes of increased liquidity. This prolonging and shortening, and consequently the length of low and high activity episodes, is more pronounced in NP and in Phase II. These observations are generally consistent with the observation that estimates of δ_1 are greater than δ_2 in both markets and phases under the IST-BCACD(G) model where trading intensity is used as the threshold variable. The same estimates of δ_1 and δ_2 are also much higher in NP than ECX and generally lower in Phase II. These results imply a trading momentum in that expected duration is shorter following high intensity trades, while trading frequency decreases following low intensity trades. Finally, since average duration is much shorter in Phase II than in Phase I (Table 1) then these episodes of activity and inactivity are much shorter lived in Phase II.

Estimate of the smoothness parameter g by SEST-BCACD(G) is significant in ECX I but not in ECX II, while it is insignificant in NP I but significant in NP II. Its value is much higher in NP than in ECX. Lower values of this parameter in SEST-BCACD indicate smoother transition between short and long duration regimes. Accordingly, the transition is smoother in ECX II than in ECX I and in NP I than in NP II. It is also smoother overall in ECX than in NP. A smoother transition is an indication of greater market depth since more hybrid transactions occur between regimes of long and short past duration and, consequently, episodes of long and short durations are not as sharply distinguished. Specifically, the interplay between informed and relatively uninformed traders is revealed in hybrid transactions, and this is expected with greater market depth (Easley and O'Hara, 1992, and Kalaitzoglou and Ibrahim 2012). The same qualitative result is reached from similar analysis of estimates of g by the IST-BCACD where trading intensity instead of past duration is used as the threshold variable. This confirms the conclusion reached above in subsection 4.2, by analysing

estimates of $\gamma^*\lambda$, that ECX is a deeper market than NP, but it adds the important distinction that ECX has become deeper in Phase II relative to Phase I while NP has become shallower.

The ability of the markets to absorb trading shocks in duration and intensity are investigated further by looking at average duration around long duration shock trades. Panel A of Figure 3 plots duration of the ten transactions that bracket a long duration trade, where a trade is identified as a 'long duration' trade if it lies in regime 2 as identified by the value of the threshold parameter s estimated by the SEST-BCACD(G) model. The figure shows a slight increase in duration of the two transactions that immediately precede a long duration (shock) trade, which indicates the market's ability to 'anticipate' such trades to some extent. The effect of the shock trade on subsequent trades, however, is substantial, since the two or three subsequent transactions exhibit high durations relative to values prior to the shock trade. The effect instilled by the shock trade is far milder (has smaller amplitude) in ECX than in NP, and in Phase II than in Phase I (but only in ECX and not in NP). It also dissipates faster in ECX than in NP, and in Phase II than in Phase I (again only in ECX and not in NP). Specifically, in ECX I it takes four subsequent transactions for duration to revert back to levels experienced prior to the shock trade, while in ECX II it takes only two subsequent transactions. In NP I it takes five subsequent transactions for duration to revert back to levels experienced prior to a shock trade, while in NP II it takes even more. Thus, shocks are milder and dissipate faster in ECX and in Phase II.

Similar but clearer results are observed when trading intensity, instead of past duration, is used as the threshold variable. Panel B of Figure 3 plots duration of the ten transactions that bracket a high intensity trade, where a high intensity trade is defined as a trade that lies in regime 2 of trading intensity as identified by the value of the threshold parameter s estimated by the IST-BCACD(G) model. The figure shows that the effect of the intensity shock trade is superseded by trades of decreasing duration, with this decrease starting as far back as four or five transactions prior to the shock trade. Thus, trading intensity seems to be more informative than duration in predicting shock trades. Market participants seem able to anticipate shocks in trading intensity earlier than shocks in duration, and since the difference between intensity and duration is volume, then volume carries important information about imminent fast trading episodes. It is clear from Panel B of Figure 3 that

the trough occurs at $t+1$, which is the transaction that immediately follows the shock trade. Duration then increases gradually over subsequent transactions and reverts back four trades later ($t+4$) to the levels that existed four or five trades prior to the shock trade. This effect is roughly the same across phases, except that duration in both markets is lower and intensity higher in Phase II than Phase I. The last four columns of Table 4 present test results showing that the decrease in average duration of the five transactions that follow a high trading intensity shock is statistically significant relative to average duration of the five transactions that precede the shock trade (p -values are all less than 0.03 in all markets and phases), but the increase in volume, though consistent across markets and phases, is not statistically significant. This last result confirms the observation (from Panel B of Figure 3) that changes in volume start prior to a shock trade, but changes in duration (Panel A, Figure 3) largely occur after a shock trade. Accordingly, the market seems better at anticipating variations in trading intensity than just duration, and more so in Phase II. This points to the incremental importance of volume in predicting trade duration and is consistent with the better in-sample fit of IST-BCACD over that of SEST-BCACD.

These results indicate that ECX has become deeper and faster at absorbing trade shocks in Phase II, while NP has become shallower and slower at absorbing trade shocks. The results also clearly reveal the existence of two types of episodes (clusters or momentum effects in duration) in the EUA market: increased intensity episodes of heightened activity, characterised by decreased duration with prior increase in volume, and decreased intensity episodes of depressed activity, characterised by increased duration. These episodes differ across markets and across phases and mainly in amplitude more than the number of transactions over which they occur (on average episodes occur over five to eight transactions).

4.4 Price volatility during activity episodes

Given the existence of these duration and intensity episodes it is of interest to see whether price volatility, measured by the standard deviation of log price change (*i.e.*, realised return volatility), is affected during these episodes. This would reveal whether there a price impact during these episodes. Panels A and B of Figure 4 plot volatility of the ten transactions that bracket a long duration

trade and a high intensity trade, respectively. Panel A shows that volatility decreases (increases) in the run up to (following) a long duration shock in ECX I, NP I and NP II. Note that these are less liquid phases (and market, viz., NP). In ECX II in which most trades occur, however, volatility increases slightly from transaction $t-5$ to transaction $t-1$ prior to a long duration shock and fluctuates around, roughly, the same level thereafter. Panel B shows a clearer picture – volatility stays at a roughly constant level prior to a high intensity shock but increases over the three transactions that follow. It reverts back to prior levels only at the fourth subsequent transaction ($t+4$). The scale of the y-axes also shows that Phase I was more volatile than Phase II. The last column of Table 4 presents test results that confirm the statistical significance of the increase in volatility following a high intensity trade in both markets and phases (associated p -values are all less than 0.04). Accordingly, the inactive episodes of increased duration and the active episodes of increased intensity are associated with a subsequent increase in price volatility. Hence, variations in liquidity have a statistically significant impact on price volatility, and volatility as a function of time and trading intensity is, at least partially, predictable in the carbon market, especially prior to high activity episodes.

4.5 OTC transactions

The particular characteristics of OTC transactions and their role in trading activity are investigated further in this section. As discussed in Section 4 above, the BCACD-OTC(G) is the best fitting model amongst those considered. Estimates of the parameter zeta, ζ , reported in Tables 2 and 3 are significantly positive for both markets and phases. Hypotheses tests, reported in the lower section of Tables 2 and 3, reject the null that ζ is zero. This indicates that OTC transactions are distinct and have a significant and positive effect on expected duration. Further, this effect is more significant than the effects of non-linearity investigated in the previous sections. In addition, OTC trades represent 36%, 18%, 44% and 42% of trades in ECX I, ECX II, NP I and NP II, respectively (calculated from the numbers tabulated in Panel A of Figure 5). These percentages show that OTC trades are a sizable proportion of total trades, especially in Phase I. Further, Panel C of Figures 3 and 4, show that duration and volatility, respectively, increase substantially immediately after an OTC trade, and the effects dissipate only after three transactions (at $t+4$) or more, with faster dissipation in ECX than NP.

Test values (p -values of the difference after-before) reported in Table 4 further confirm that the increase in duration and volatility, as well as a decrease in intensity and volume, that immediately follow an OTC trade are statistically significant (with p -values at 0.04 or lower and those for volume are 0.07 or lower). Accordingly, OTC trades, which are relatively large in number, cause an immediate increase in duration and price volatility and a decrease in intensity and volume.

These results for OTC trades are in contrast with the decrease in duration and increase in volume and intensity that follow a high intensity trade, as reported in the last four columns of Table 4 and discussed in Sections 4.2 and 4.3. It is important to note, therefore, that not all high intensity transactions are OTC trades. Panel C of Figure 5 shows that 16.6%, 18.7%, 33.8% and 24.9% of high intensity trades in ECX I, ECX II, NP I and NP II, respectively, are OTC trades. Further, Panel B of Figure 5 shows that 8.4%, 32.8%, 11.9% and 9.8% of OTC trades in these respective markets are high intensity trades. Hence, most OTC trades are, in fact, low intensity trades. In particular, comparing the entries in Table 4 for OTC trades against those for high intensity trades, shows clearly that average duration, volume and volatility are far higher, and intensity lower, around OTC trades than around high intensity trades. This implies that non-OTC high intensity trades, which are more in number (Panels A and B of Figure 5), have, on average, lower duration, volume and volatility and higher trading intensity than OTC trades. Therefore, most OTC trades seem to occur during different trading episodes than most high intensity trades. Both episodes increase price volatility, but the episodes that are permeated by OTC trades have, on average, more than double the volatility of episodes that are permeated by non-OTC high intensity trades. Accordingly, it is likely that OTC trades have a significant role to play in liquidity, since their relative size is large, and in information, since they have a large effect on price volatility.

The presence of these two different episodes calls for further investigation of their relative intensity dynamics and price effects. Figure 6 plots the average trading intensity of the five transactions before ($t-5$ to $t-1$), the five transactions after ($t+1$ to $t+5$) and transactions six to ten ($t+6$ to $t+10$) after an OTC trade, where all transactions occurring in a market phase are dissected into 'low' and 'high' trading intensity regimes determined by the value of the threshold variable, s , estimated by IST-BCACD for that market phase. This attempts to gauge any difference between the short and long

term impact of OTC trades during different regimes of trading activity. The figure shows that average trading intensity of the five transactions that follow an OTC trade is invariably lower than that of the five transactions that precede the trade, regardless of whether these trades are in a low or a high intensity regime. This verifies that the same result shown in Table 4 over all OTC trades, is robust across different intensity regimes. Figure 6, however, shows that the average intensity of transactions six to ten that follow an OTC trade increase substantially to levels higher than those of the five trades that precede the OTC trade, but this increase occurs only in the high intensity regime. In the low intensity regime, instead, average trading intensity either continues to decrease or does not rise by much. Thus, unlike other high intensity trades, OTC trades seem to initially slow down market activity, and occur during relatively higher volatility episodes. The small proportion that occurs during high intensity regimes has a substantial long term effect. The initial slowing down of activity can be either because of a depletion in liquidity (depth), since OTC trades are larger than non-OTC trades, or possibly due to the introduction of price related information that requires the market more time to resolve fully. This latter possibility is investigated next through an analysis of the transitory and permanent components of the price impact of OTC trades.

Figure 7 plots the transitory and permanent components of price impact around an OTC transaction. This is presented for the low and high intensity regimes for each market phase. These components are calculated as in Frino et al. (2010) and are regarded in the microstructure literature (*c.f.*, Madhavan, 2000) as the main measures of liquidity and information effects of the impact of trading.²¹ The liquidity effect is regarded as 'transitory' because it measures the price impact difference between transaction $t+5$ and the average over transactions $t-5$ to $t-1$, and the information effect is regarded as 'permanent' because it measures the price impact difference between transactions $t+5$ and $t-5$. A few patterns are clear from Figure 7. First, both components increase, often substantially, following an OTC trade. Second, given the relative scales of the graphs, the impact of an OTC trade is greater in NP than in ECX. Third, the permanent information-related effect of an

²¹ Analogous to Berkman et al. (2005), Frino et al. (2010) define the temporary 'impact cost' component as $Temporary_{i,t} = [(price_{t+5} - VWAP\ Price_i) / MinTick] * D_i$, and the permanent component as $Permanent_{i,t} = [(price_{t+5} - price_{t-5}) / MinTick] * D_i$, where $price_{t-5}$ is the price of the trade five transactions prior to OTC trade i , $price_{t+5}$ is the price of the trade five transactions after OTC trade i , $MinTick$ is the minimum price increment, D_i is 1 for buys and -1 for sells and $VWAP\ Price_i$ is the volume-weighted average price of the five transactions that immediately precede OTC trade i . Also see Frino and Oetomo (2005).

OTC trade is much greater than the transitory liquidity-related effect. Finally, the relative impact of an OTC trade is usually greater in Phase I than in Phase II, especially in the larger ECX market. Accordingly, OTC trades seem to have a dual role. In the long term (over ten transactions) they carry price-related information and in the short term (over five transactions) their relatively larger size depletes market liquidity. OTC trades cause both temporary and permanent price changes, but the long term information effect is greater, however. This is consistent with the observations made above from Table 4 and Figure 6. In particular, trading intensity decreases immediately ($t+1$ to $t+4$) following an OTC trade, but subsequently (in trades $t+6$ to $t+10$) increases to levels higher than before the OTC trade. The decrease in average volume immediately following the OTC trade (Table 4) also suggests that, on average, smaller trades follow, and this is accompanied by a large upward price adjustment. This suggests that the effect of liquidity depletion is transitory relative to the effect of information. Moreover, Panel C of Figure 4 shows that volatility reverts back to levels experienced prior to the OTC trade in about three or four subsequent trades, while the effect on intensity takes more than six to ten subsequent trades in order to dissipate. On average, therefore, volatility calms down faster than trading intensity following an OTC trade. This suggests a quicker resolution of price uncertainty (information) than increased trading activity (liquidity), which is a sign of efficiency. The same result, however, also implies a possible delayed learning process for some market participants who trade faster six to ten transactions after an OTC trade albeit with little effect on price volatility. The presence of participant groups with slower learning is indeed reported by Kalaitzoglou and Ibrahim (2012) in an analysis that identifies groups of trading agents through patterns in non-price related order flow variables. The results reported here contribute by presenting evidence that price uncertainty is resolved faster than it takes for the associated increase in activity to dissipate.

5. Conclusion

The Carbon market appears to be structurally different from other liquid and well established financial markets. During Phase I and the beginning of Phase II the market was relatively new, rather illiquid and politically influenced. The contract under examination, which is the most heavily traded, has a long time to maturity and is being traded in various markets in overlapping periods. This study

investigates the role of liquidity in the identification of trading episodes through duration models that incorporate characteristics of order flow. Potential structural differences between the two largest exchanges (ECX and NP) and between phases I and II are examined, with particular emphasis on the role of non-linearity, asymmetry and OTC transactions in trading patterns. The post-trade impact of these on liquidity and volatility is also examined.

The main findings highlight the importance of liquidity in the trading process in the Carbon market. Trading activity seems to follow a momentum in two major types of episodes: high intensity episodes, characterized by decreased duration with prior increase in volume, and low intensity episodes, characterized by increased duration. Both episodes are associated with a subsequent increase in price volatility and are much shorter lived in Phase II. Variations in liquidity, therefore, are relevant to price, and reflect, at least partially, the resolution of uncertainty. This is faster in Phase II. Further, OTC transactions are distinct from other trades, including high intensity trades. Unlike other high intensity trades OTC trades seem to slow down market activity in the short term, and occur during relatively higher volatility episodes. Evidence is presented that OTC trades have a dual effect. In the long term (over ten transactions) they carry price-related information, and in the short term (over five transactions) their larger size depletes market liquidity. Both transitory and permanent components of price impact increase following an OTC trade, but the permanent information-related effect is much greater. Consequently, trading episodes might begin or stop because of information transmission or interflow between the OTC and the organized non-OTC markets. However, the sensitivity of market participants towards both effects – non-linear asymmetries and OTC transactions – varies considerably across the two different trading environments, and is closely related to liquidity. ECX appears to be a deeper, more liquid and more mature market than NP since liquidity and volatility shocks are smaller in magnitude and are absorbed faster. The effect instilled by a duration shock, for example, is far milder in ECX than in NP and in Phase II than in Phase I. Changes in volume start prior to a shock in trading intensity, but changes in duration largely occur after the trade. In ECX Phase II it takes only two subsequent transactions for duration to revert back to the levels experienced prior to the shock trade, while by contrast, in NP Phase II it takes up to five subsequent transactions. ECX has become deeper in Phase II relative to the more volatile Phase I while NP has

become shallower, especially towards the fourth quarter of 2008. Accordingly, liquidity enhancing measures would enhance market viability and would lead to more accurate pricing, thereby assisting EU ETS to serve its purpose, which is the reduction of CO₂ emissions.

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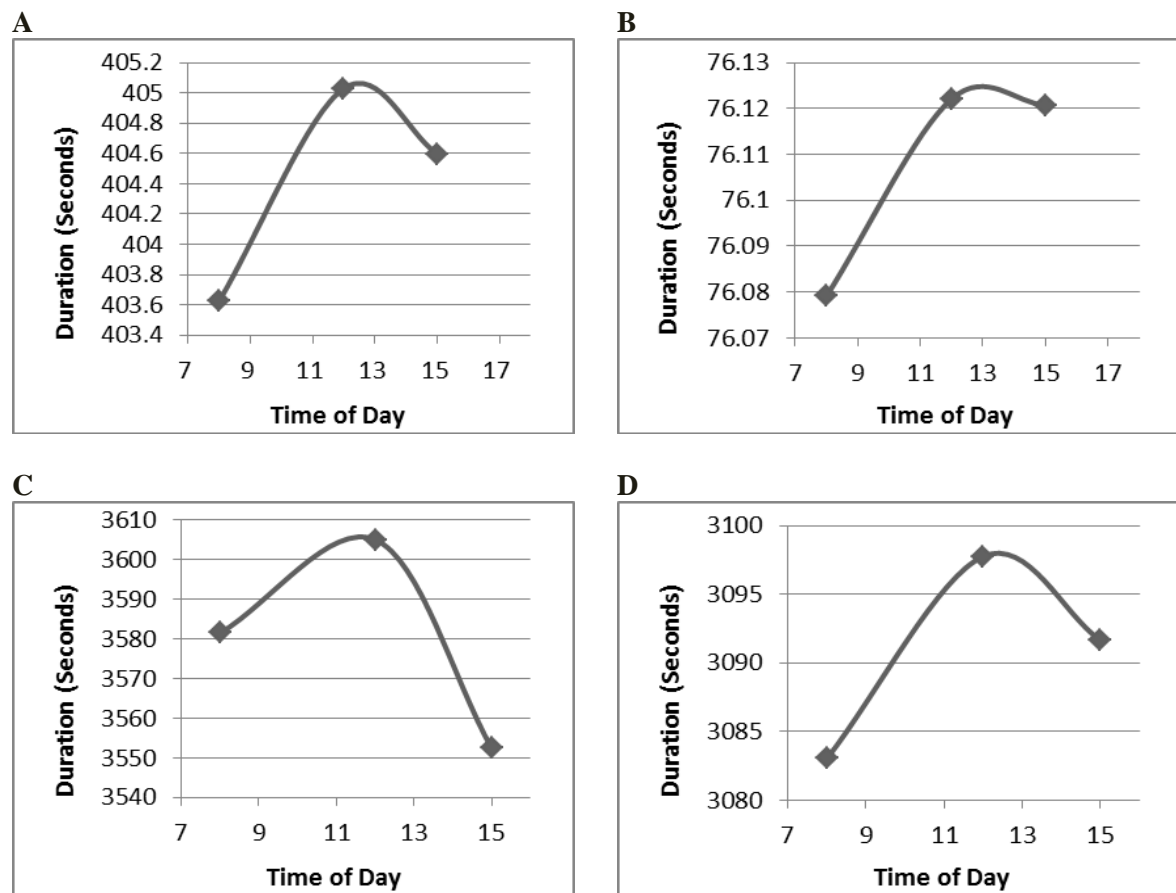
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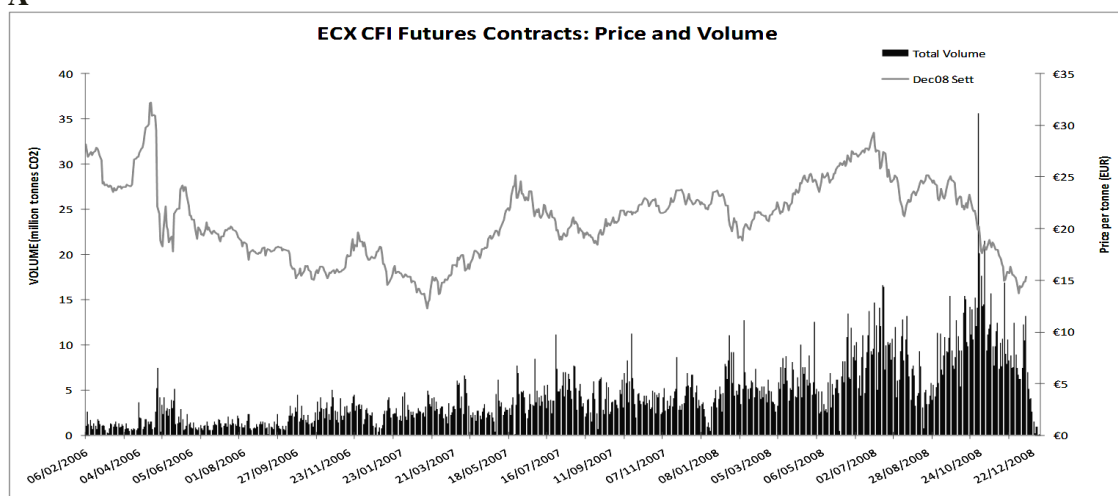
Figure 1 Intraday pattern of duration



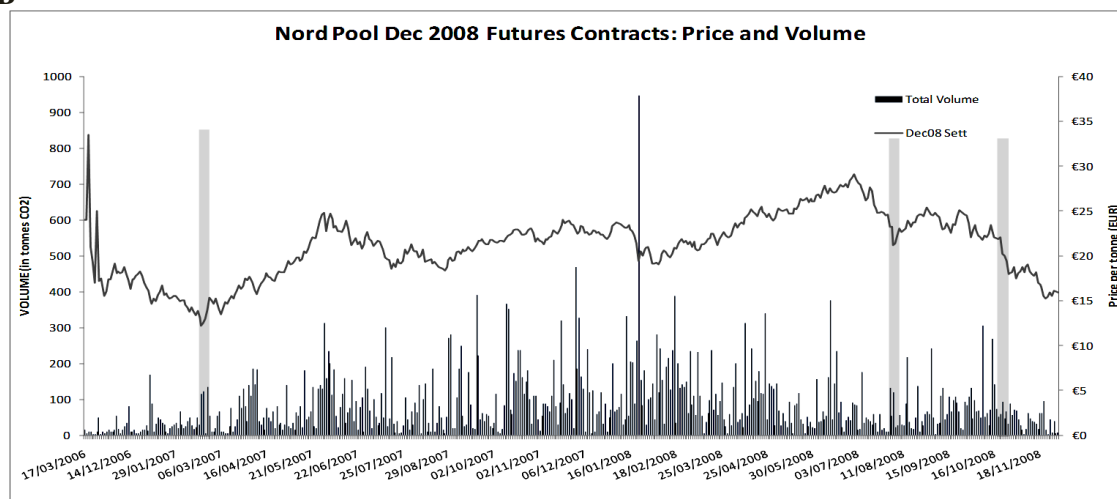
The figure presents the intraday pattern of actual durations in both markets and phases. Panel A is ECX Phase I, Panel B is ECX Phase II, Panel C is NP Phase I, and Panel D is NP Phase II.

Figure 2 Price, volume and trade imbalance

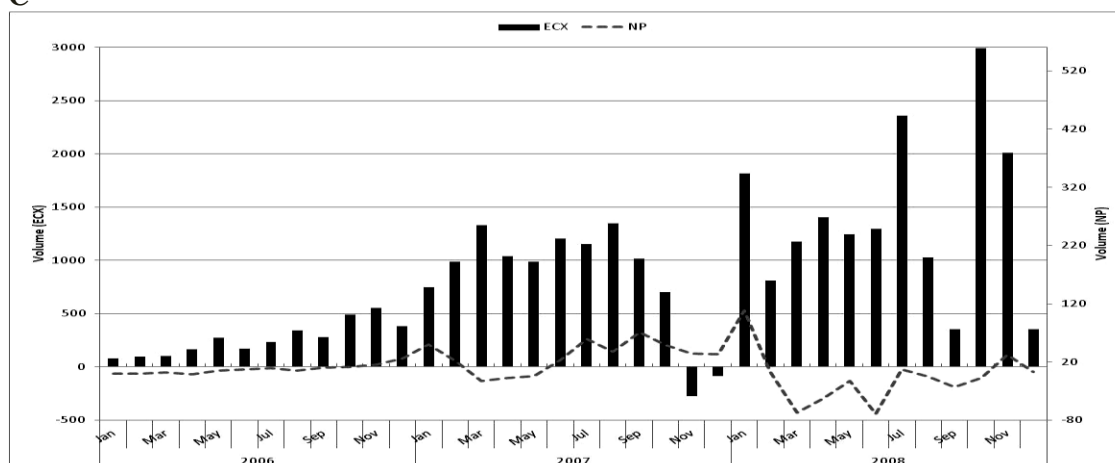
A



B

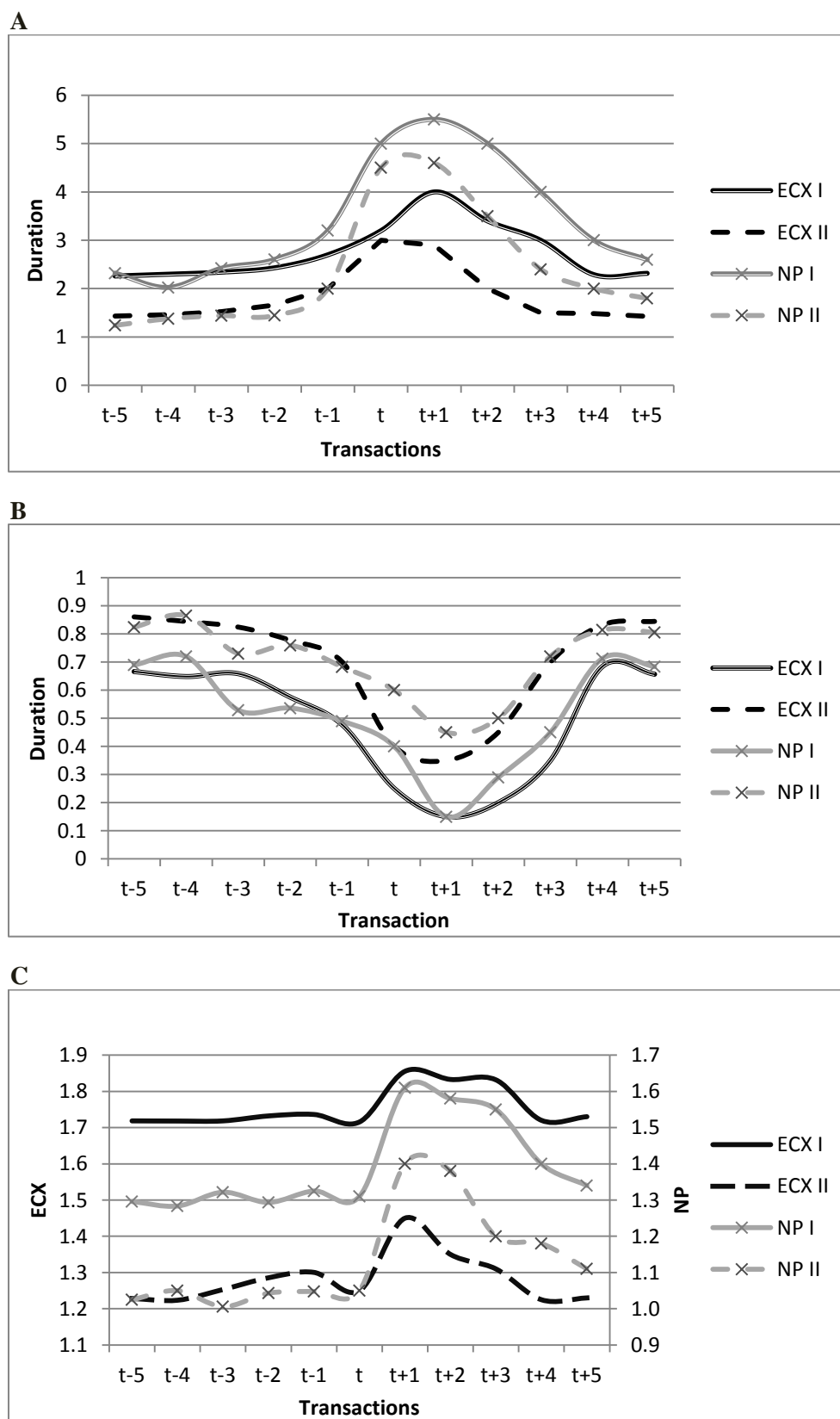


C



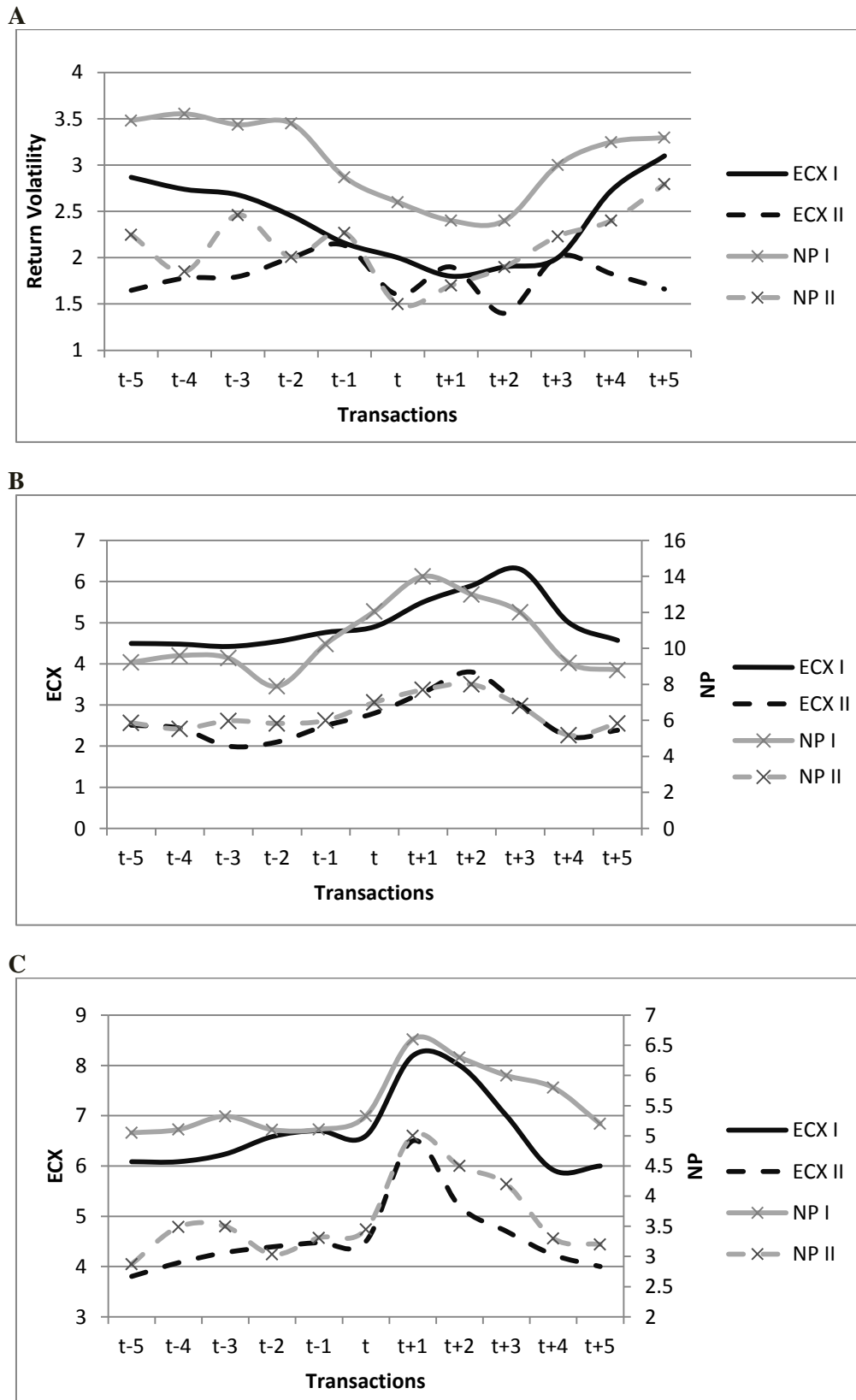
Panels A and B exhibit daily price and aggregate volume of the December 2008 futures contract over the period 2006-2008 in ECX and NP, respectively. Panel C exhibits the trade imbalance (number of buyer less number of seller initiated transactions) over the same period in ECX and NP.

Figure 3 Average duration around long duration, high trading intensity and OTC transactions



The figure exhibits average (across all trades in the sample) duration of each of the ten transactions that bracket: (A) a long duration shock, (B) a high trading intensity shock, and (C) an OTC transaction.

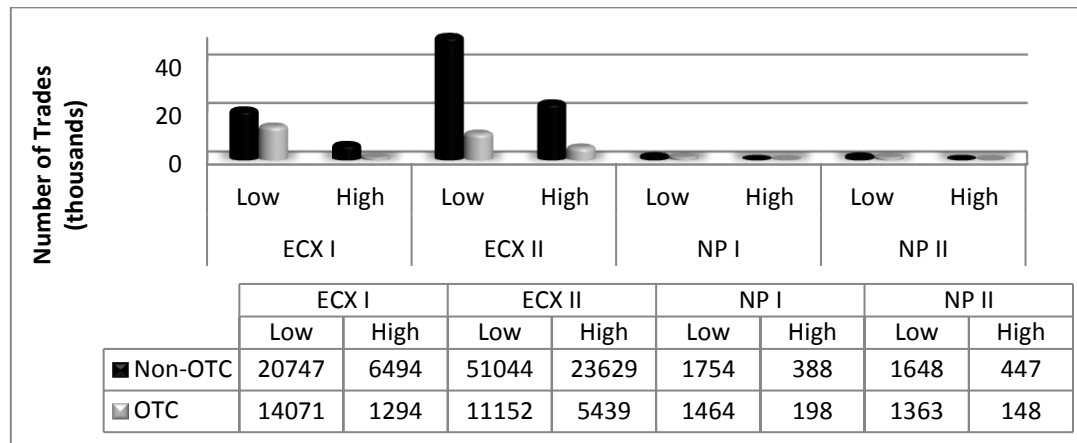
Figure 4 Price volatility around long duration, high trading intensity and OTC transactions



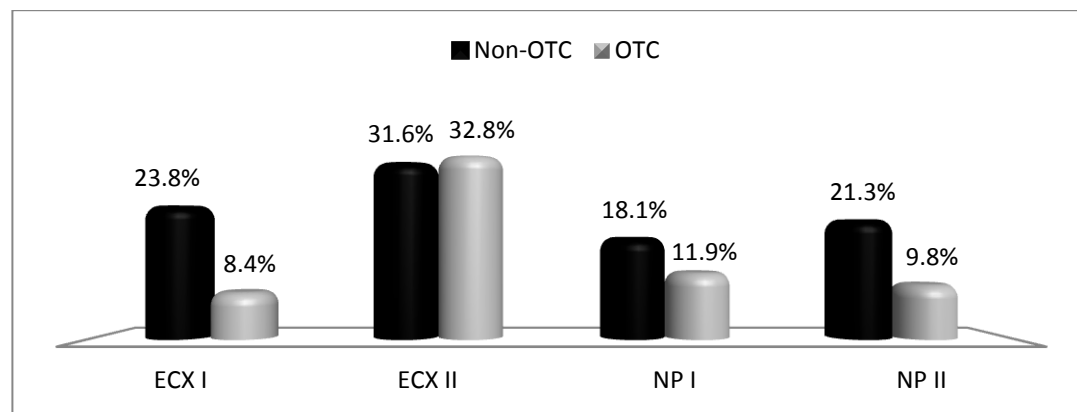
The figure exhibits average (across all trades in the sample) price volatility of each of the ten transactions that bracket: (A) a long duration shock, (B) a high trading intensity shock, and (C) an OTC transaction.

Figure 5 Number and proportion of OTC and non-OTC trades by intensity regime

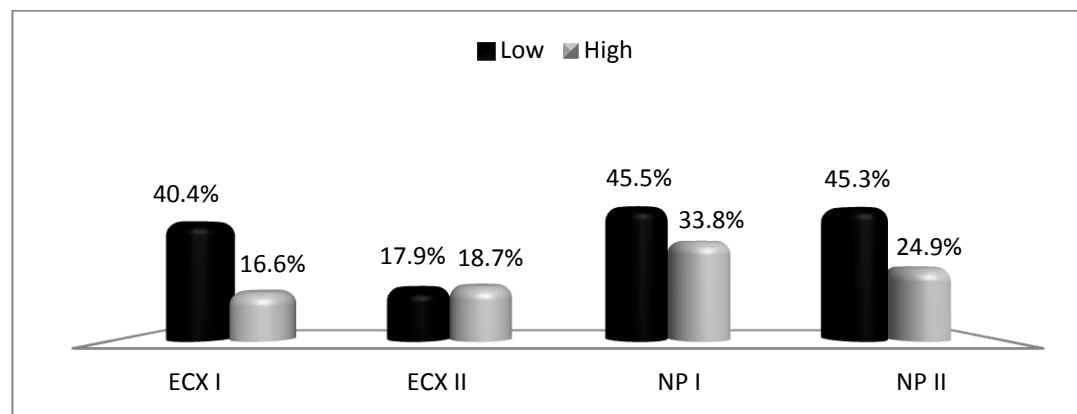
A



B

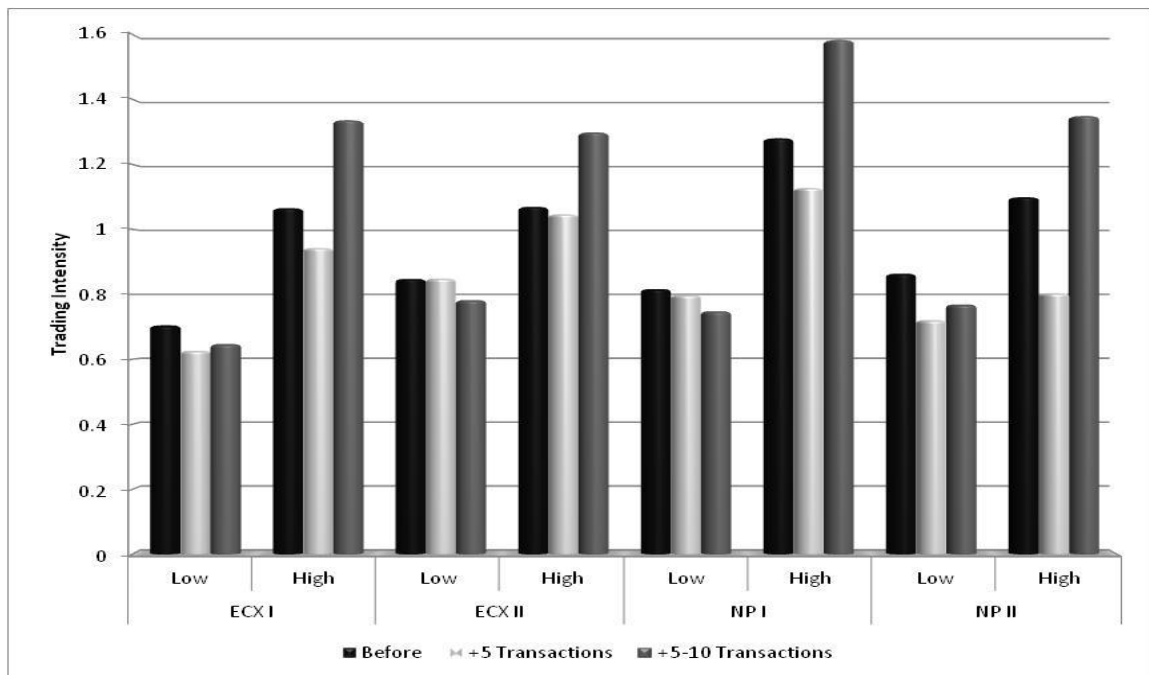


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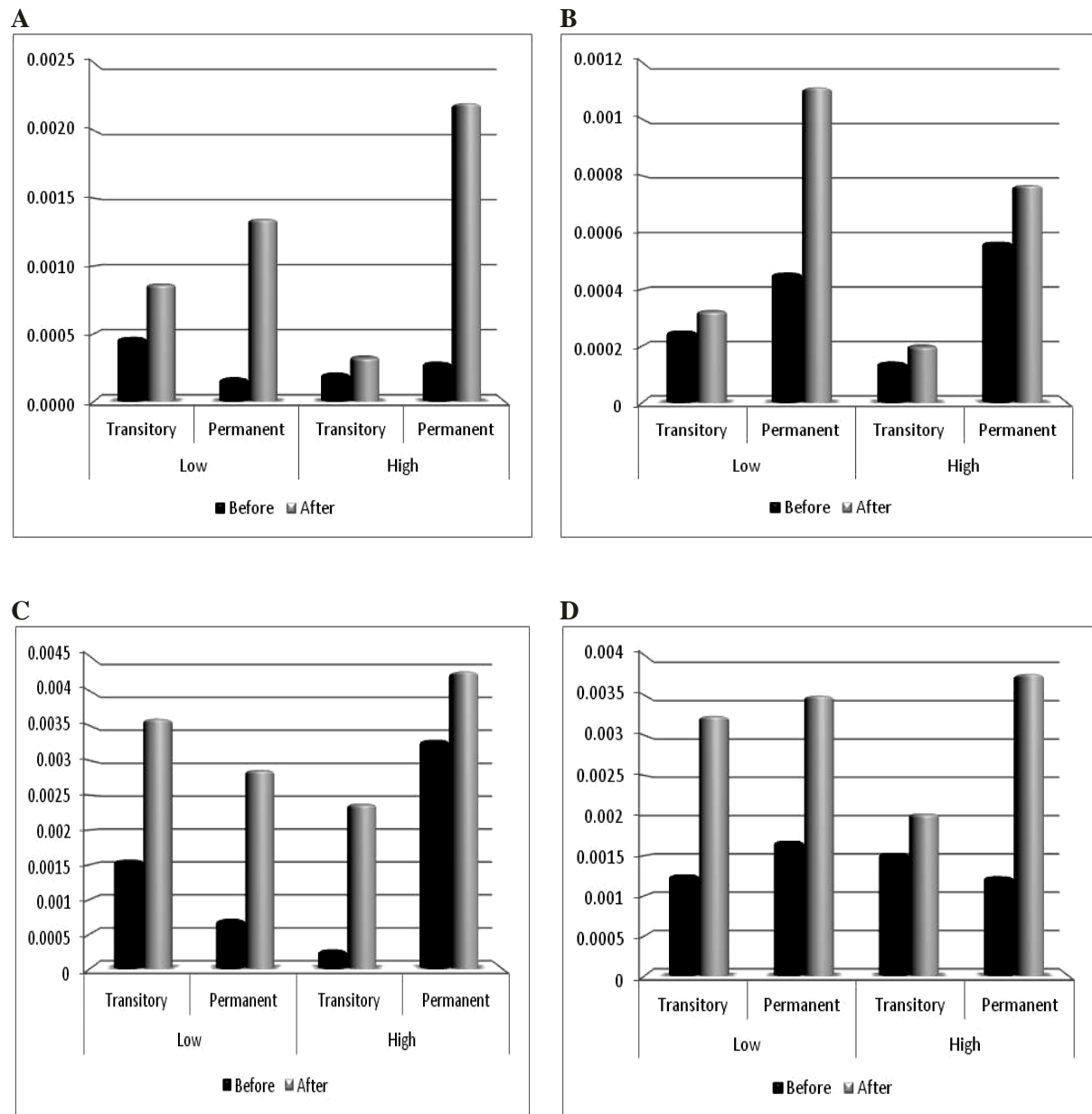
Panel A shows the number of trades by trade indicator (OTC or non-OTC) and trading intensity (high and low) in each market and phase. The numbers are also tabulated. Panel B shows the proportion of non-OTC trades that are high intensity (*i.e.*, number of high intensity non-OTC trades/number of total non-OTC trades), and the proportion of OTC trades that are high intensity. Panel C shows the proportion of low intensity trades that are OTC trades (*i.e.*, number of low intensity OTC trades/total number of low intensity trades), and the proportion of high intensity trades that are OTC trades.

Figure 6 Average trading intensity around OTC transactions



The figure shows average trading intensity of the 5 transactions that immediately precede an OTC trade (Before), the 5 transactions that immediately follow an OTC trade (+5 Transactions) and the 6th to 10th transactions that follow an OTC trade (+5-10 Transactions). Values are categorised by high and low trading regimes within each market phase.

Figure 7 Price impact components of OTC transactions



This figure presents the transitory and permanent price impact components around OTC transactions. This is presented for each market phase and categorised by high and low trading intensity regimes (as identified by estimation results presented in Table 2). These components measure the temporary and permanent price effects associated with OTC trades as defined in footnote 21. Both component measures are scaled by the minimum tick. Panel A is ECX I, Panel B is ECX II, Panel C is NP I, and Panel D is NP II.

Table 1 Basic statistics

	ECX I						ECX II					
	Actual			Diurnally			Actual			Diurnally		
	Actual	Volume	Actual	Price	Diurnally	Adjusted	Actual	Volume	Actual	Price	Diurnally	Adjusted
	Duration	(No of	Trading	(In Euros)	Adjusted	Trading	Duration	(No of	Trading	(In Euros)	Adjusted	Trading
	(Seconds)	Contracts)	Intensity		Duration	Intensity	(Seconds)	Contracts)	Intensity		Duration	Intensity
Mean	375.87	12.45	0.69	19.85	1.16	0.98	75.73	9.69	1.12	22.60	1.01	1.01
Median	79	10	0.11	20.40	0.25	0.15	23	5	0.25	22.85	0.3	0.21
Maximum	30979	500	53.00	33.70	110.25	78.93	4332	500	104	32.35	62.67	96.27
Minimum	1	1	0.00	10.75	0.00	0.00	1	1	0.00	11.16	0.01	0
Std. Dev.	1264.1	18.16	2.13	2.97	3.87	3.02	157.15	19.4	3.18	3.33	2.09	2.79
Skewness	11	10.93	8.56	0.37	10.86	8.67	7.29	11.02	10.77	0.41	7.99	10.58
Kurtosis	168.44	216.24	121.38	2.74	165.71	124.43	109.26	198.51	210.47	2.65	137.48	203.04
	NP I						NP II					
	Actual			Diurnally			Actual			Diurnally		
	Actual	Volume	Actual	Price	Diurnally	Adjusted	Actual	Volume	Actual	Price	Diurnally	Adjusted
	Duration	(No of	Trading	(In Euros)	Adjusted	Trading	Duration	(No of	Trading	(In Euros)	Adjusted	Trading
	(Seconds)	Contracts)	Intensity		Duration	Intensity	(Seconds)	Contracts)	Intensity		Duration	Intensity
Mean	1912.21	10.81	0.27	20.33	1	1.06	1370.57	10.67	0.27	22.73	0.95	1.01
Median	480	10	0.02	21.20	0.25	0.03	540	10	0.02	22.92	0.38	0.056
Maximum	29933	250	15.00	33.50	17.52	71.92	20542	308	15	37.25	17.54	71.92
Minimum	1	1	0.00	12.00	0	0	1	1	0.00	1.00	0	0
Std. Dev.	3727.12	11.77	1.09	3.00	1.99	3.92	2195.64	14.5	1.09	2.80	1.54	3.92
Skewness	3.71	7.07	7.10	0.64	4.05	8.55	3.28	9.28	7.10	0.35	3.68	8.56
Kurtosis	19.69	92.87	61.60	2.78	23.56	100.11	17.63	130.03	61.60	4.47	23.85	100.11

The table presents basic statistics of the variables under examination. These include the mean, median, maximum, minimum, standard deviation, skewness and kurtosis for all samples of markets and phases.

Table 2 Estimation results: ECX Phase I and Phase II

ECX I												ECX II												
Models	BCACD			SEST-BCACD			IST-BCACD			BCACD-OTC			BCACD			SEST-BCACD			IST-BCACD			BCACD-OTC		
	E	W	G	E	W	G	E	W	G	E	W	G	E	W	G	E	W	G	E	W	G	E	W	G
Coefficients																								
<i>omega</i>	-0.1783 (-6.92)	-0.3741 (-9.80)	-1.8384 (-8.54)	-0.1290 (-9.19)	-0.2535 (-6.85)	-1.7009 (-5.41)	-0.1347 (-6.69)	-0.2810 (-8.55)	-2.2934 (-3.62)	-0.1711 (-6.96)	-0.3463 (-10.22)	-1.3651 (-10.20)	-0.3778 (-11.06)	-0.7564 (-12.30)	-3.2812 (-5.26)	-0.3091 (-12.99)	-0.6258 (-11.88)	-2.3955 (-7.27)	-0.3114 (-12.88)	-0.6053 (-12.37)	-2.0981 (-10.96)	-0.3649 (-12.77)	-0.6964 (-13.31)	-2.0810 (-9.47)
<i>alpha</i>	0.2174 (6.84)	0.4496 (10.11)	2.0691 (9.24)	0.1905 (8.81)	0.3543 (7.61)	1.9353 (6.06)	0.1937 (6.92)	0.3755 (9.69)	2.5167 (3.38)	0.1790 (6.70)	0.3702 (9.83)	1.4859 (10.65)	0.4679 (11.56)	0.8889 (13.30)	3.5173 (5.62)	0.3941 (13.50)	0.7580 (13.06)	2.6356 (7.93)	0.3983 (13.05)	0.7385 (13.59)	2.3406 (12.13)	0.4420 (13.22)	0.7960 (14.03)	2.2348 (10.03)
<i>zeta</i>										0.0595 (7.06)	0.0992 (10.38)	0.2801 (20.92)										0.0437 (5.44)	0.1167 (15.03)	0.3203 (31.07)
<i>delta</i>	0.5434 (21.21)	0.4081 (19.86)	0.1332 (9.72)							0.5915 (21.38)	0.4501 (21.10)	0.1816 (12.37)	0.3896 (17.41)	0.2551 (15.16)	0.1174 (5.21)							0.4068 (20.83)	0.2813 (16.64)	0.1190 (9.85)
<i>delta 1</i>				0.4707 (16.28)	0.3928 (19.54)	0.1286 (6.92)	1.1861 (19.77)	0.6833 (9.98)	0.1466 (6.08)							0.3786 (20.60)	0.2523 (15.02)	0.0989 (0.73)	0.5080 (17.39)	0.3381 (16.45)	0.1207 (10.40)			
<i>delta2</i>				1.2394 (11.86)	0.8003 (9.07)	0.1463 (5.49)	0.4935 (5.04)	0.4082 (21.33)	0.1031 (15.76)							0.5107 (15.99)	0.3233 (12.89)	0.2936 (2.69)	0.3844 (16.76)	0.2560 (13.78)	0.0834 (10.51)			
<i>beta</i>	0.9740 (92.57)	0.9466 (55.00)	0.8837 (30.17)	0.9877 (51.50)	0.9647 (43.21)	0.8842 (27.80)	0.9828 (58.14)	0.9570 (47.81)	0.8829 (30.30)	0.9653 (69.90)	0.9335 (60.31)	0.8384 (56.35)	0.9080 (67.30)	0.8718 (54.99)	0.8258 (53.13)	0.9159 (63.64)	0.8771 (51.13)	0.8266 (63.15)	0.9145 (71.75)	0.8771 (40.21)	0.8284 (60.70)	0.9012 (60.61)	0.8518 (57.43)	0.7634 (42.55)
<i>g</i>				4.5118 (2.91)	6.1052 (2.44)	5.9850 (2.81)	3.8299 (0.98)	2.3254 (2.15)	1.1698 (2.78)							1.5066 (1.34)	2.0784 (1.42)	2.0146 (1.17)	2.3074 (1.86)	1.9474 (2.11)	1.6592 (1.02)			
<i>s</i>				1.0625 (11.55)	1.0150 (7.19)	1.0045 (8.69)	0.7783 (7.33)	0.8838 (5.97)	0.9065 (6.89)							2.1682 (11.84)	2.3865 (23.56)	2.1778 (12.61)	0.4051 (13.94)	0.4517 (19.47)	0.5377 (8.35)			
<i>γ</i>		0.6627 (23.06)	0.1924 (18.61)		0.6650 (29.37)	0.1932 (20.08)		0.6640 (25.23)	0.1902 (16.89)		0.6637 (29.04)	0.1965 (38.64)		0.6611 (39.46)	0.1991 (54.47)		0.6614 (37.20)	0.1991 (46.36)		0.6614 (37.25)	0.1992 (44.50)		0.6609 (49.90)	0.1999 (51.76)
<i>λ</i>			10.2259 (9.83)			10.1474 (10.24)			10.4548 (8.98)			10.9840 (19.65)			11.8453 (23.87)			10.4985 (29.77)			10.3584 (28.48)			9.9298 (34.48)
<i>L</i>	-29465	-21402	-20181	-29227	-21348	-20181	-29329	-21374	-20180	-29275	-21291	-19932	-77442	-59501	-55165	-77363	-59480	-55155	-77360	-59473	-55144	-77378	-59381	-54665
<i>BIC</i>	1.3841	1.0059	0.9488	1.3737	1.0041	0.9491	1.3785	1.0053	0.9490	1.3755	1.0010	0.9374	1.6976	1.3045	1.2097	1.6962	1.3045	1.2098	1.6962	1.3043	1.2096	1.6963	1.3021	1.1988
H(0)																								
<i>zeta=0</i>										49.88 (0.00)	107.70 (0.00)	437.48 (0.00)										29.58 (0.00)	225.85 (0.00)	965.10 (0.00)
<i>delta=1</i>	317.71 (0.00)	829.60 (0.00)	2063.44 (0.00)							218.09 (0.00)	664.90 (0.00)	3105.53 (0.00)	743.65 (0.00)	1958.41 (0.00)	4209.12 (0.00)							923.02 (0.00)	1806.61 (0.00)	5317.06 (0.00)
<i>γ=1</i>		16592 (0.00)	7364 (0.00)		15782 (0.00)	7033 (0.00)		20825 (0.00)	5171 (0.00)		21451 (0.00)	10704 (0.00)		37837 (0.00)	5720736 (0.00)		41355 (0.00)	3827346 (0.00)		28062 (0.00)	3052941 (0.00)		63210 (0.00)	5057331 (0.00)
<i>λ=1</i>			90.42 (0.00)			85.21 (0.00)			65.91 (0.00)			550.89 (0.00)			1044.09 (0.00)			1171.22 (0.00)			1108.49 (0.00)			1010.50 (0.00)
<i>γ=λ=1</i>			1201960 (0.00)			1232191 (0.00)			1120516 (0.00)			541689 (0.00)			5734443 (0.00)			3827370 (0.00)			3053508 (0.00)			5057332 (0.00)

The first section of the table presents parameter estimates and *t*-stats (in parenthesis) of four models each estimated in three versions of different error distributions for ECX Phase I and Phase II. The second section presents the maximum Log-likelihood function value (*L*) and the Bayesian Information Criterion $BIC = [-2*(L) + k*ln(R)]/R$, where *k* is the number of estimated parameters and *R* is the number of observations. The last section presents hypothesis tests (Wald tests) on parameters of interest. The values in parentheses in this third section are associated *p*-values.

Table 3 Estimation results: Nord Pool Phase I and Phase II

NP I												NP II												
Models	BCACD			SEST-BCACD			IST-BCACD			BCACD-OTC			BCACD			SEST-BCACD			IST-BCACD			BCACD-OTC		
	E	W	G	E	W	G	E	W	G	E	W	G	E	W	G	E	W	G	E	W	G	E	W	G
Coefficients																								
<i>omega</i>	-0.3959 (-3.68)	-0.6100 (-3.95)	-0.9445 (-3.05)	-0.3792 (-4.09)	-0.5840 (-3.88)	-0.9782 (-18.47)	-0.3395 (-3.82)	-0.5620 (-3.06)	-0.9236 (-4.68)	-0.4323 (-3.54)	-0.7010 (-11.51)	-1.2033 (-3.94)	-0.4563 (-2.43)	-0.6776 (-2.54)	-0.7738 (-3.60)	-0.3002 (-3.11)	-0.4743 (-3.00)	-0.5364 (-3.16)	-0.2987 (-3.35)	-0.4278 (-3.41)	-0.4796 (-3.36)	-0.4843 (-2.35)	-0.7557 (-3.23)	-0.9202 (-2.88)
<i>alpha</i>	0.4775 (3.74)	0.7270 (4.11)	1.1293 (3.36)	0.4635 (4.14)	0.7030 (4.08)	1.1608 (14.47)	0.4433 (4.31)	0.6904 (3.60)	1.1111 (5.15)	0.4606 (3.47)	0.7308 (9.55)	1.2589 (3.99)	0.5457 (2.59)	0.7972 (2.78)	0.9097 (3.93)	0.4012 (3.35)	0.6093 (3.34)	0.4599 (3.59)	0.4129 (3.57)	0.5818 (3.96)	0.6526 (3.89)	0.5441 (2.49)	0.8129 (3.40)	0.9827 (2.98)
<i>zeta</i>										0.1119 (2.52)	0.1831 (5.80)	0.2897 (6.37)										0.0653 (2.45)	0.1348 (3.89)	0.1686 (4.90)
<i>delta</i>	0.4145 (5.76)	0.3272 (4.77)	0.2384 (3.47)							0.3823 (5.00)	0.2855 (11.95)	0.1869 (3.92)	0.2860 (3.16)	0.2262 (2.87)	0.2064 (4.95)							0.2662 (2.92)	0.1962 (3.40)	0.1678 (2.83)
<i>delta 1</i>				0.3535 (4.81)	0.2986 (4.25)	0.1399 (2.23)	0.6013 (6.11)	0.3801 (5.08)	0.3645 (2.88)							0.2656 (3.14)	0.1998 (2.59)	0.1793 (3.40)	0.6069 (3.02)	0.4801 (3.04)	0.4385 (3.30)			
<i>delta2</i>				0.4571 (5.68)	0.3528 (4.62)	0.3281 (6.07)	0.3973 (3.15)	0.3248 (2.66)	0.2266 (2.09)							0.5512 (3.26)	0.3827 (3.29)	0.3494 (3.36)	0.2523 (3.18)	0.1909 (3.26)	0.1710 (3.56)			
<i>beta</i>	0.8943 (30.43)	0.8696 (31.70)	0.8482 (32.39)	0.8969 (30.54)	0.8715 (30.29)	0.8474 (41.51)	0.8976 (32.23)	0.8720 (31.95)	0.8489 (32.98)	0.8705 (25.41)	0.8322 (40.63)	0.7914 (30.76)	0.7890 (10.81)	0.7727 (14.30)	0.7676 (12.12)	0.8404 (13.63)	0.8069 (13.50)	0.7996 (15.13)	0.8262 (14.68)	0.8049 (14.61)	0.7977 (14.51)	0.7696 (10.14)	0.7416 (12.97)	0.7297 (15.71)
<i>g</i>				10.5006 (1.70)	9.4302 (1.64)	10.0314 (0.28)	4.2546 (2.19)	7.3534 (1.79)	6.9540 (0.81)							8.5006 (3.70)	9.3534 (2.18)	9.9002 (2.13)	2.4758 (3.96)	2.7121 (2.99)	2.8036 (2.91)			
<i>s</i>				1.5875 (8.92)	2.3260 (25.86)	2.9797 (0.96)	0.7198 (2.39)	0.7577 (3.86)	0.8038 (8.35)							2.6766 (17.42)	3.3260 (15.86)	3.9797 (13.96)	0.6051 (13.94)	0.7326 (15.86)	0.6038 (8.35)			
<i>γ</i>		0.6280 (14.27)	0.3534 (12.59)		0.6282 (9.50)	0.3527 (13.74)		0.6283 (18.44)	0.3543 (16.24)		0.6286 (11.98)	0.3257 (12.25)		0.6369 (11.80)	0.5431 (15.10)		0.6374 (77.20)	0.5442 (14.97)		0.6379 (8.64)	0.5463 (15.00)		0.6368 (9.63)	0.5194 (15.48)
<i>λ</i>			2.7681 (6.89)			2.7768 (7.69)			2.7560 (8.96)			3.2336 (6.69)			1.3042 (9.11)			1.3014 (9.37)			1.2950 (9.60)			1.4064 (9.90)
<i>L</i>	-2814	-1917	-1881	-2812	-1917	-1881	-2812	-1920	-1884	-2801	-1907	-1863	-3297	-2530	-2527	-3289	-2528	-2525	-3288	-2526	-2523	-3294	-2526	-2521
<i>BIC</i>	1.4883	1.0190	1.0019	1.4934	1.0253	1.0083	1.4935	1.0269	1.0099	1.4837	1.0158	0.9948	1.8376	1.4148	1.4153	1.8399	1.4201	1.4206	1.8393	1.4192	1.4198	1.8382	1.4145	1.4140
H(0)																								
<i>zeta=0</i>										16.33 (0.00)	19.16 (0.00)	40.57 (0.00)										12.11 (0.00)	18.37 (0.00)	25.23 (0.00)
<i>delta=1</i>	66.20 (0.00)	22.74 (0.00)	12.06 (0.00)							65.17 (0.00)	94.47 (0.00)	290.47 (0.00)	62.32 (0.00)	96.25 (0.00)	362.15 (0.00)							65.00 (0.00)	194.57 (0.00)	196.24 (0.00)
<i>γ=1</i>		3815 (0.00)	531 (0.00)		3195 (0.00)	636 (0.00)		2321 (0.00)	876 (0.00)		3361 (0.00)	644 (0.00)		3369 (0.00)	161 (0.00)		1928 (0.00)	157 (0.00)		2532 (0.00)	155 (0.00)		3231 (0.00)	205 (0.00)
<i>λ=1</i>			19.39 (0.00)			24.21 (0.00)			32.57 (0.00)			21.34 (0.00)			4.51 (0.03)			4.71 (0.03)			4.79 (0.03)			8.18 (0.00)
<i>γ=λ=1</i>			19322.4 (0.00)			17513 (0.00)			13813 (0.00)			25766.6 (0.00)			1876.12 (0.00)			1734 (0.00)			3067 (0.00)			2464.97 (0.00)

The first section of the table presents parameter estimates and *t*-stats (in parenthesis) of four models each estimated in three versions of different error distributions for NP Phase I and Phase II. The second section presents the maximum Log-likelihood function value (*L*) and the Bayesian Information Criterion $BIC = [-2 * (L) + k * \ln(R)] / R$, where *k* is the number of estimated parameters and *R* is the number of observations. The last section presents hypothesis tests (Wald tests) on parameters of interest. The values in parentheses in this third section are associated *p*-value

Table 4 Average duration, volume, trading intensity and price volatility around OTC and high intensity transactions

		OTC				Trading Intensity			
		Duration	Volume	Trading Intensity	Return Volatility	Duration	Volume	Trading Intensity	Return Volatility
ECX I	Before	1.6495	14.9769	0.7310	6.1646	0.6646	11.6652	1.4920	3.0747
	After	1.8469	14.9224	0.6498	6.5462	0.6402	11.7954	1.5442	3.2127
	<i>p</i>	(0.01)	(0.06)	(0.02)	(0.02)	(0.00)	(0.04)	(0.01)	(0.02)
ECX II	Before	1.2284	14.8024	0.9321	4.3270	0.8372	9.9181	1.2392	2.4864
	After	1.2725	14.7400	0.9014	4.5680	0.8199	9.9858	1.2515	2.6064
	<i>p</i>	(0.04)	(0.07)	(0.04)	(0.04)	(0.03)	(0.08)	(0.04)	(0.04)
NP I	Before	2.2308	12.8354	0.4637	7.3909	0.6540	10.2675	1.5484	1.3610
	After	2.3820	13.4617	0.4146	9.4076	0.6256	10.3571	1.7959	1.5679
	<i>p</i>	(0.01)	(0.04)	(0.01)	(0.00)	(0.01)	(0.07)	(0.00)	(0.01)
NP II	Before	1.0223	10.9568	0.8805	5.1923	0.8200	10.5937	1.5927	1.4776
	After	1.0326	10.8886	0.8270	6.0323	0.7941	10.6489	1.6165	1.5068
	<i>p</i>	(0.02)	(0.04)	(0.03)	(0.02)	(0.03)	(0.14)	(0.02)	(0.02)

This table presents average duration, volume, trading intensity and return volatility before (five prior transactions) and after (five subsequent transactions) an OTC and a high trading intensity transaction. This is presented for each market phase. The values in parentheses are *p*-values of tests on $H_0: (value_{after} - value_{before}) = 0$, which test whether there are significant differences in the variables around a trade.